“Does Austerity kill? “

An Empirical Analysis of Portuguese Hospitals

Work Project

submitted by

Hendrik Schiermeyer

M.Sc. Economics
Prof. Pedro Pita Barros
NOVA SBE
T4 2018/2019

Abstract

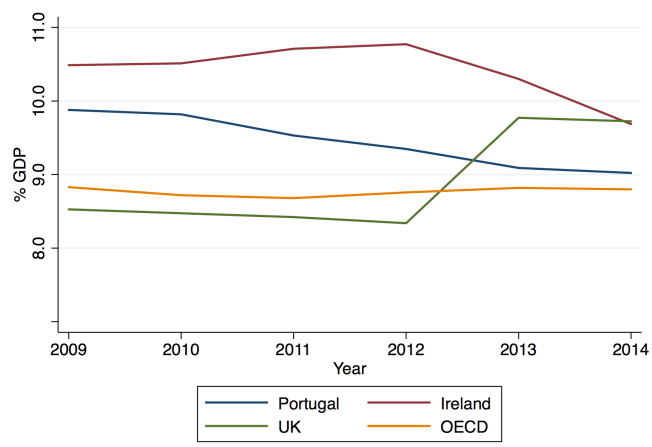
This paper examines the impact of austerity in Portuguese hospitals on mortality. Using combined data obtained from the National Health Service and the Central Administration of the Health System in Portugal we estimate a probit model. Empirical results suggest an inverse relationship between financial resources and mortality, robust across the different groups of hospitals defined by the NHS. To our knowledge, this paper is the first to examine the impact of financial hardship on institutional level on hospital mortality in Portugal.

Keywords: Austerity, Arrears, Mortality, Hospital Financing
JEL Codes: I10, I15, I18

1. Introduction

The empirical literature and consequently also policy makers are still not sure whether fiscal austerity or a different policy is the right answer for a country's success in economic recovery after a recession. While countries like Ireland, the UK or Portugal have more or less voluntarily opted for fiscal austerity in the recent past, other countries like Iceland chose a different path and thus, neglected the IMF's austerity demands.[1] In Portugal, total savings of €670 million in health care were demanded as a condition of the memorandum of understanding between the troika and the Portuguese government (Karanikolos, et al., 2013). Health expenditure as a percentage of GDP decreased over the 2009 – 2015 period from 9.9% in 2009 to 8.9% in 2014 (Figure 1)[2]. This significant decrease is probably a result of the austerity policies on public health spending. Since welfare cuts in the mentioned countries were targeted mainly at the individual level (e.g. by increasing citizens' copayments[3]), little research has been done on the impact of austerity measures applied at the institutional level on (hospital) mortality. In this paper, we use payment arrears as a proxy for austerity at the institutional level. The underlying theory behind using payment arrears goes as follows: Austerity measures applied at the institutional level (e.g. hospital level) may result in underfunding of the institutions which in turn may lead to accumulation of payment arrears. The aim of this paper is to explore the "costs" of bad man-

Figure 1: Health expenditure as % of GDP



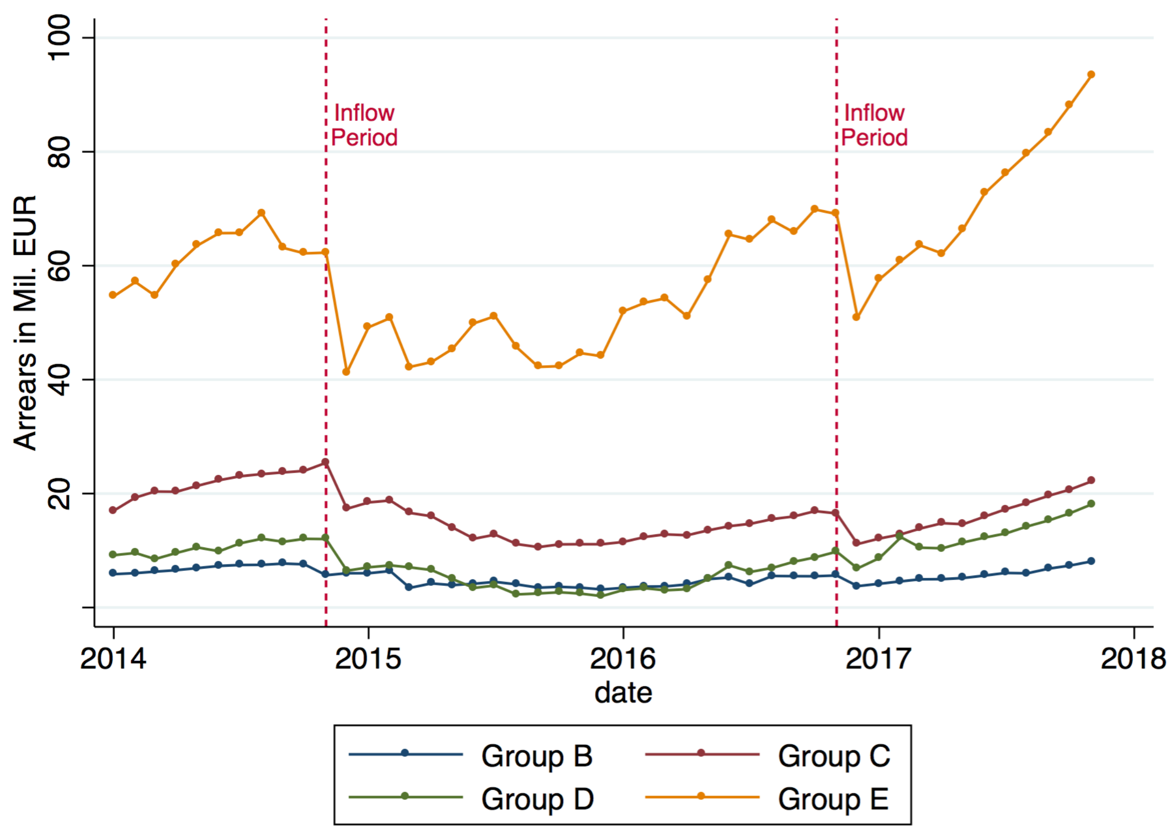
Source: OECD Health statistics. Current expenditure on health (all functions). All providers.

[1] See The Guardian (2017).
[2] Source: Organisation for Economic Co-operation and Development. Current expenditure on health (all functions). All providers. Own representation.
[3] See Augusto (2012).

agement created by arrears and debt in Portuguese public hospitals funded by the National Health Service.

Therefore, we make use of a unique dataset provided by the Portuguese National Health System in combination with information on financial performance of the respective public hospitals. The consideration of payment arrears is particularly useful since the Portuguese government made extraordinary transfer payments to hospitals at different occasions. This fact is shown in Figure 2 by the two red vertical lines.[4]

Figure 2: Development of Payment Arrears by Hospital Groups



This circumstance allows us not only to measure whether higher arrears have a negative impact but also whether compensation payments, by contrast, have had a positive impact. By the

[4] Source: Serviço Nacional de Saúde (Portuguese National Health System). Average monthly payment arrears of public hospitals by predefined groups. Own representation. See Appendix 1 for group division.

means of a probit model we first test the hypothesis whether austerity increases in-hospital mortality. Moreover, we test whether policies against fiscal austerity or to put it another way, attenuate austerity measures, decrease in-hospital mortality.

The remainder of this paper is organized as follows. Section 2 describes the Portuguese National Health System in terms of its structure and financing strategy of public hospitals. Section 3 reviews the literature associated with the impact of austerity measures on (hospital) mortality. Section 4 describes the methodology used for the empirical analysis. Section 5 and 6 present our results and robustness checks. Finally, section 7 presents our conclusions.

2. The Portuguese National Health System

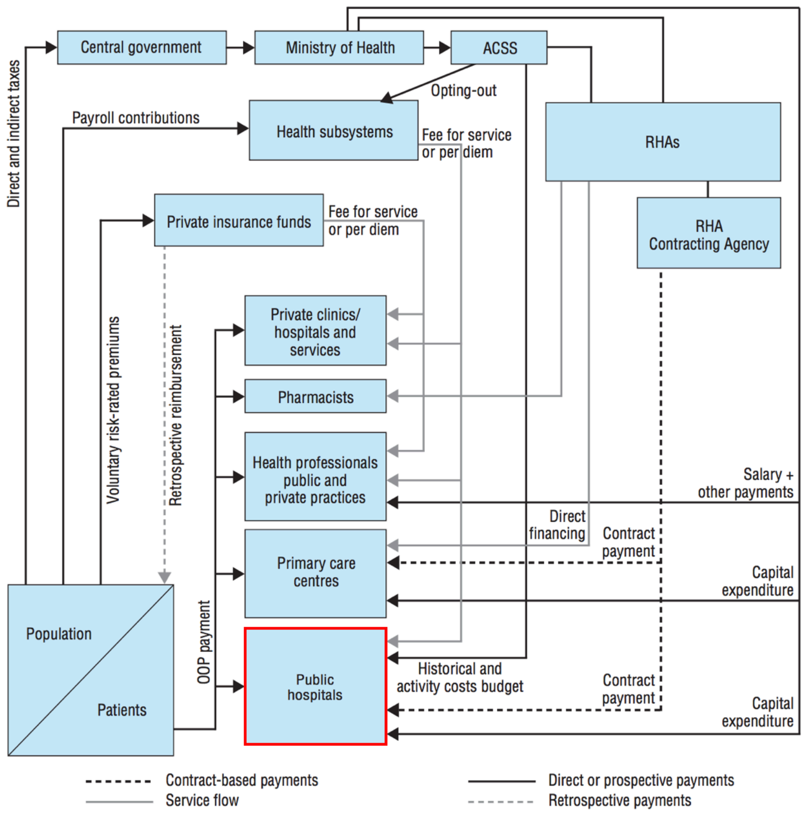
2.1 Structure of the National Health System

The Portuguese National Health System (Portuguese: Serviço Nacional de Saúde) was created in 1979 and operates under the supervision of the Ministry of Health. It is managed by the Central Administration of the Health System (ACSS). The NHS is structured into the following five health regions/regional health administrations: North, Center, Lisbon and Tagus Valley, Alentejo and Algarve. While the ACSS is responsible for central management functions and the establishment of health polices, the regional administrations' primary responsibility is to provide the healthcare services to the population and to execute the national health plan (Simões, Augusto, Fronteira, & Hernández-Quevedo, 2017). Primary health care is provided mainly by so-called Health Center Groups (Portuguese: Agrupamentos de Centros de Saúde) subdivided into several health centers, which do usually cover one municipality. Secondary and tertiary care is provided mainly by hospital establishments. In 2014, Portugal had 209 hospitals, 113 of which belonged to the NHS with a total capacity of 25,000 beds in public hospitals and 10,500 beds in private hospitals (European Observatory on Health Systems and Policies, 2018). Observed trends in other European countries are also present in Portugal, as for example a decreasing number of private hospitals due to recent mergers between public sector hospitals and the closing of psychiatric hospitals. Moreover, Portugal faces similar challenges regarding the distribution of health workers across the population such as the United Kingdom. They are concentrated in the major urban and coast-line centres (Lisbon, Coimbra and Porto) leaving the inland underserved (Simões, Augusto, Fronteira, & Hernández-Quevedo, 2017) and thus, creating a mismatch between health resources and patient characteristics (European Observatory on Health Systems and Policies, 2018).

2.2 NHS Financing Strategy

We omit here a detailed description of the financial developments in the Portuguese health care system but instead focus on the financing mechanisms of public hospitals covered by the NHS. Figure 1 shows the main refinancing mechanisms of the relevant institutions.[5]

Figure 3: Financial flows



[5] Adapted from Barros, Machado & Simões (2011)

To a large extent, the Portuguese NHS is financed by general taxation. "Hospital budgets are drawn up and allocated by the Ministry of Health through the ACSS" (Simões, Augusto, Fronteira, & Hernández-Quevedo, 2017). Since 1997, these budgets are so-called activity-based allocations, involving DRG information, hospital outpatient volume and case-mix adjustments for ambulatory surgery (Barros, Machado, & Simões, 2011). However, given limited incentives to encourage cost efficiency, a group classification based on principal component analysis was introduced. Regarding maintenance and development of infrastructure, all public entities including hospitals ought to outline an annual plan for activities and budget in which should be included the largest investment (European Observatory on Health Systems and Policies, 2018). In 2012, a compulsory request for hospital/primary care investment authorization was introduced. "This compulsory request is applied to all public entities for investments above €1 million or above €100,000 if they have debts. These investments are then analyzed by the central administration for health (ACSS)" (European Observatory on Health Systems and Policies, 2018).

3. Literature Review

To our knowledge, this study is the first to link payment arrears of Portuguese hospitals to quality outcomes. However, if we abstract from the two constraints we are able to identify relevant literature estimating relationships between austerity measures and quality of health care outcomes in different countries.

Loopstra et al. (2016) examine whether budgetary reductions in Pension Credit and social care in the UK account for rises in mortality rates among pensioners aged 85 years and older. The UK government "sought cuts totaling £85 billion" which "resulted in a net reduction in welfare expenditure of £16.7 billion" (Loopstra et al., 2016). Using a multiple linear regression model that is comparable to the method used here, the authors identified a strong relationship between declines in Pension credit spending and increasing old-age mortality. While Loopstra et al. focus on austerity schemes applied at individual level, this paper aims at explaining the influence austerity schemes applied at institutional level might have on mortality. Aiken et al. (2014) examine the relationship between a so called soft target in reducing hospital operating expenses – nurse staffing – and hospital mortality in nine European countries. In particular, the authors assess "whether differences in patient to nurse ratios and nurses' educational qualifications in nine of the 12 RN4CAST countries with similar patient discharge data were associated with variation in hospital mortality after common surgical procedures" (Aiken, et al., 2014).[6] They find significant results for the hypothesis that cuts in nurse staffing to reduce operating expenses of hospitals adversely affects patient outcomes measured by 30 day in-hospital mortality. In a similar study, Aiken et al. (2011) examine how hospital nurse staffing, nurse education, and work environment are associated with patient outcome. They find a decrease in the odds on both deaths and failure-to-rescue in hospitals with average work environments and even larger decreases in hospitals with the best work environments.

While the above cited studies focus on rather specific causes and/or austerity measures, there is a vast amount of literature which examines more macroeconomic connections between austerity and health care. In a more recently published book by Stuckler and Basu (2013), the authors deal with historical case studies ranging from 1930s America to present-day Greece and summarise empirical evidence about those to show how government policies affect quality of health care and thus, mortality. A study mentioned in the book of Stuckler and Basu is the one of Karanikolos et al. (2013) on the interplay between the financial crisis, austerity and health in Europe. The authors analyse and compare how different reactions of countries like Greece,

---

[6] RN4CAST is a think-tank that studies how organizational features of hospital care impact on nurse recruitment, nurse retention and patient outcomes (http://www.rn4cast.eu/about1.html).

Spain or Portugal that adopted strict fiscal austerity and countries like Iceland that rejected fiscal austerity measures affected health. Karanikolos et al. conclude that “austerity measures can exacerbate the short-term public health effect of economic crises”. Moreover, they favour the hypothesis, that it is not an economic crisis itself causing escalating health and social crises in Europe but the combination of economic shocks and fiscal austerity.

To sum up the literature review, the research studies conducted on the impact of austerity measures on health outcomes have constantly focused on different explanatory variables than the ones used in this paper. While the analysis of the effect of payment arrears on hospital mortality is a novelty in health economics, especially in Portugal, the methodology used in this paper is a common and approved approach that will be presented below.

4. Methodology

4.1 Data

As stated in the introduction, the main dataset comes from the Serviço Nacional de Saúde (National Health Service in Portugal). It is managed by the Central Administration of the Health System (ACSS). The dataset contains all patients treated in Portuguese hospitals that belong to the NHS. Besides general patient level information as age, gender or treatment outcome, several other information is included. The dataset enables a sequence-based examination of treated patients. Each sequence – also referred to as an episode – follows the Diagnosis-Related Groups (DRG) patient classification, which is a case grouping that summarizes patients with similar costs.[7] The Portuguese DRG system breaks down 25 major categories which are subdivided into 669 diagnoses.[8] Moreover, the dataset contains hospital level information which is later on used to control for hospital specific effects.

---

[7] For additional information on Diagnosis-Related Groups see Busse et al. (2011)
[8] This level allows a financial quantification of the sequence. (Average) costs for the individual codes

Further, we used information on financial performance of Portuguese hospitals, also provided by the NHS. This dataset contains the relevant arrears variable, recorded monthly from January 2014 to May 2018. It measures the monthly level of payment arrears to external creditors for 49 Portuguese hospitals. Additionally, we included two smaller datasets provided by the NHS which contain relevant control variables on hospital and patient level. More precisely, these two datasets refer to yearly hospital utilization and readmission rates of patients. A detailed overview of the variables included in the analysis can be found in Appendix 2.

For the analysis performed, we have selected an outcome measure of hospital quality as our dependent variable. "Outcome quality measures compare the number of patients who experience a given outcome to the number expected to experience the outcome" (Doyle, Graves, & Gruber, 2017). In line with the health economics literature, we use in-hospital mortality when assessing the effect of austerity on Portuguese hospitals' quality, which is the most commonly used indicator (Gobillon & Milcent, 2017). Moreover, mortality is one of the quality indicators approved by the Agency for Healthcare Research and Quality and can therefore be used to examine differences in quality between hospitals (Agency for Healthcare Research and Quality, 2002). Even though the literature shows a number of drawbacks using in-hospital mortality as a quality indicator for hospital performance, we consider the advantages to be more important.[9] In particular, as it is the most serious clinical outcome, it makes sense to use mortality as quality indicator. Moreover, there is no coding difference in mortality rates as it is the case in different outcome measures (Hentschker & Mennicken, 2012).

Before discussing the empirical approach used, the cleansing and construction process of our dataset will be outlined. Table 1 shows the development of our dataset in terms of the number of observations.

---

can be calculated via tables provided by the NHS.

[9] We forego an in-depth discussion at this point and refer to Doyle et al. (2017)

Table 1: Overview of Cleansing & Dataset Construction Process

Cleansing stage	Observations
Base dataset	6 855 703
Merge arrears data	5 532 915
Merge readmission data	5 264 365
Merge utilization data	5 243 086
Drop erroneous utilization data	5 224 280
Creation of lagged values	4 172 024
Creation of Δ-Arrears values	4 046 207
Adjust DRGs in-sample	2 474 639

The base dataset consists of 6,855,703 observations. After merging the base dataset with the arrears, 1,322,788 observations were dropped primarily due to missing arrears data for specific hospitals. Following merging this new dataset with readmission and utilization data, 268,550 and 21,279 observations were dropped, respectively. Due to the creation of lagged values of arrears, 1,052,256 observations were removed since no values can be generated for values prior to October 2014. A further elaboration of the lagged values is presented in Section 4.2. The same applies to the creation of changes in arrears for each month, which removed a further 125,817 observations. Finally, 1,571,568 observations were dropped according to the following DRG selection criteria, applied cumulatively. DRGs with a non-positive mortality rate were excluded. DRGs representing at least 1% of the whole sample were kept. Moreover, DRGs with a mortality rate greater or equal to 1% paired with a number of observations greater or equal to 100 were also kept.

Therefore, the final dataset is made up of 2,474,639 observations. Table 2 provides descriptive statistics of the dataset whereby monetary variables *Arrears, l1_Arrears, l2_Arrears, l3_Arrears* and *delta_Arr* are expressed in million EUR.

Table 2: Mean Statistics across Hospital Groups

Variable	Group B	Group C	Group D	Group E	Group F	Other
age	68,53	67,44	65,82	62,27	59,39	67,93
male	0,54	0,5	0,52	0,5	0,45	0,5
severity2	0,33	0,42	0,43	0,37	0,38	0,45
severity3	0,1	0,11	0,09	0,1	0,02	0,14
severity4	0,02	0,03	0,02	0,03	0	0,03
utilization	0,81	0,87	0,89	0,86	0,82	0,9
hosp_south	0	0	0,18	0	0	0
FEB	0,09	0,09	0,08	0,09	0,08	0,09
MAR	0,09	0,08	0,08	0,09	0,08	0,09
APR	0,08	0,08	0,08	0,08	0,08	0,09
MAY	0,08	0,08	0,08	0,08	0,08	0,09
JUN	0,08	0,08	0,08	0,08	0,08	0,09
JUL	0,07	0,08	0,08	0,08	0,08	0,08
AUG	0,07	0,07	0,08	0,07	0,08	0,08
SEP	0,07	0,08	0,08	0,08	0,09	0,09
OCT	0,08	0,08	0,08	0,08	0,08	0,09
NOV	0,1	0,1	0,11	0,1	0,11	0,09
DEC	0,09	0,08	0,08	0,08	0,08	0,06
JUL_south	0	0	0,015	0	0	0
AUG_south	0	0	0,015	0	0	0
Arrears	6,37	14,57	8,46	61,87	5,19	0,14
l1_Arrears	6,49	14,89	8,08	60,89	4,01	0,28
l2_Arrears	6,7	15,3	7,88	60,56	3,17	0,36
l3_Arrears	6,88	15,74	7,73	60,05	2,44	0,53
delta_Arr	-0,01	-0,04	0,16	0,65	0,44	-0,03
inflow_2014	0,98	0,98	0,97	0,97	0,97	1
inflow_2016	0,28	0,32	0,31	0,28	0,17	0,33

Appendix 1 shows the division of the public hospitals into hospital groups based on the classification by the NHS.

4.2 Empirical Strategy

We perform our analysis on patient level since the dataset contains several relevant control variables to account for differences between patients which makes it easier to isolate a potential effect of arrears on mortality. Moreover, performing the analysis on patient level allows us to estimate a more precise mortality variable which does not rely on mortality figures provided by the hospitals.[10]

The binary outcome variable is equal to 1 if the patient died in the hospital and zero otherwise (e.g. the patient left the hospital or was transferred to a different hospital). In addition to

[10] This avoids, for example, that single hospitals have to be dropped for reasons such as missing data.

a probit model estimated by maximum likelihood estimation we also estimate a linear probability model (LPM) estimated by OLS which works as a robustness check. Both models estimate the following regression equation.

$$Mort_{p,h} = \beta_0 + \beta_1 patient_p + \beta_2 hospital_h + \beta_3 seasonal + \beta_4 Austerity + \varepsilon_{p,h}$$

The coefficient vector β_1 refers to the matrix of patient characteristics *patient* that controls for heterogeneity in the risk profiles of different patients. On patient level we control for age, gender and severity of diseases which is measured in four increments by the NHS, whereby a severity indicator of 4 represents the highest degree of severity, e.g. the highest risk-factor. We control for severity by three dummy variables.

The coefficient vector β_2 refers to the matrix of hospital characteristics that controls for variation between hospitals. The vector includes the variables *utilization*, *hosp_south*, *JUL_south* and *AUG_south*, explained below. By the variable *utilization* we control for the monthly occupancy rate of a hospital. The variable *hosp_south* controls for the location of a hospital, more precisely it captures the variation between hospitals located in the south of Portugal and other ones. The two interaction terms *JUL_south* and *AUG_south* control for the specificity in Portugal that a significant part of the population travels to the south of the country - the Algarve region - in summer for vacation. We assume that this will result in less severe hospitalizations, on average. Moreover, we control for monthly effects which is captured by the coefficient vector β_3 and the matrix *seasonal*.

Our initial considerations regarding the modelling of the austerity indicator are presented below. The *Austerity*-vector mentioned in the initial regression equation represents the following variables:

$$\begin{aligned} Austerity_h = {} & \lambda_1 Arrears_h + \lambda_2 Lag\ 1_h + \lambda_3 Lag\ 2_h + \lambda_4 Lag\ 3_h + \lambda_5 \Delta Arrears_h \\ & + \mu_1 Inflow\ 2014_h + \mu_2 Inflow\ 2016_h. \end{aligned}$$

The parameter λ_1 measures the impact of the monthly level of arrears on mortality. Thus, we determine hereby the direct impact of the unadjusted series. The parameters λ_2, λ_3 and λ_4 are the coefficients of the lagged values of the unadjusted series. We include lags of 3 months, 6 months and 9 months, respectively. Technically, the first lag (3 months) for a given hospital *h* and date *t* is the unadjusted arrears entry of hospital h in month *t-3*. With regard to the selection of the lags, there is no theoretical connection, as no study of this kind has been carried out to date. However, in the Technical Appendix, we show that the results do not change significantly if we use lags of 4 and 8 months instead of the ones used here. The parameter λ_5 measures the effect of the change in arrears in relation to the previous month. It is constructed by dividing the difference between the arrear entry of hospital *h* in month *t* and the arrear entry of hospital *h* in month *t-1* by the absolute value of the arrear entry of hospital h in month t-1.[11] Therefore, the parameter λ_5 captures the effect of the relative change in arrears of a hospital. In case of huge drops, caused by extraordinary transfers of money, we set the change equal to 0. More precisely, $\Delta Arrears$ follows the rule max $\{A_t - A_{t-1} + K, 0\}$ where *K* is a constant that accounts for the significant drop that we define as 25% of A_{t-1}. Thus, we are able to capture the "normal working" of a hospital. Moreover, we include two dummy variables to control for the inflow of money from the government to hospitals. We identified two relevant inflow periods in the dataset. The first in December 2014 and the second in December 2016. The dummies take a value of 1 for all periods after the extraordinary transfer of money took place.

However, high correlations between the lags of arrears and thus also the current levels of arrears led to the implication that having A_t, A_{t-3}, A_{t-6} and A_{t-9} in the same regression framework is merely adding the same information. Therefore, using A_t without lagged values should capture the main effect. A different modeling option would be to directly include a

[11] Technically: $\Delta Arrears = \frac{Arrears_{h,t} - Arrears_{h,t-1}}{|Arrears_{h,t-1}|}$

time trend instead of A_t. However, in this case other time effects will be included as well. The model adjustment is presented below.

$$Mort_{p,h} = \beta_0 + \beta_1 patient_p + \beta_2 hospital_h + \beta_3 seasonal + \boldsymbol{\delta_1} \Delta Arrears_h + \boldsymbol{\delta_2} Inflow\ 2014_h + \boldsymbol{\delta_3} Inflow\ 2016_h + \varepsilon_{p,h}$$

The conceptual work in the modelling effort of arrears - which led to the model adjustment - is presented below.

Suppose that payment arrears follow a trend: $A_t = \alpha t + \varepsilon_t$, where *t* is a time trend and ε_t is a stochastic shock. Then,

$$A_{t-1} = \alpha(t-1) + \varepsilon_{t-1} = \alpha t - \alpha + \varepsilon_{t-1}$$

$$A_{t-3} = \alpha(t-3) + \varepsilon_{t-3} = \alpha t - 3\alpha + \varepsilon_{t-3}$$

$$A_{t-6} = \alpha(t-6) + \varepsilon_{t-6} = \alpha t - 6\alpha + \varepsilon_{t-6}$$

$$A_{t-6} = \alpha(t-9) + \varepsilon_{t-9} = \alpha t - 9\alpha + \varepsilon_{t-9}.$$

Hence, *Austerity* becomes

$$Austerity_t = (\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4)A_t - \sum_i \lambda_i\, \alpha i + \sum_i \varepsilon_{t-i}$$

The term $\sum_i \lambda_i\, \alpha i$ will be captured by the constant of the regression. As a corollary, everything is captured by the coefficient of A_t. This makes the lags of arrears difficult to identify in the case of this underlying trend behind the payment arrears.[12]

The hypotheses tested are: (1) existence of a non-negative relationship between mortality and arrears $\delta_1 > 0$ and (2) existence of an inverse relationship between mortality and capital inflows $\delta_2 < 0$ and $\delta_3 < 0$. Hence, hypothesis (1) tests whether austerity, measured by the level

[12] Moreover, we considered that arrears follow a motion law. We refer to the Technical Appendix for an in-depth analysis of the arrears dynamics.

of arrears of a hospital, increases mortality. Hypothesis (2) tests whether a policy against fiscal austerity, decreases mortality.

First, we estimate the model with all hospitals. Subsequently, we estimate the model separately by the hospital groups B, C, D, E and F.[13] All models are estimated with robust standard errors adjusted for clustering effects of local hospitals.

5. Results

Table 3 shows the probit regression results for the whole sample and by the different hospital groups classified by the NHS. We report marginal effects after probit regression for the relevant variables regarding our research hypotheses.

Table 3: Probit Regression Results[14]

	Percent change in hospital mortality					
	Total	Group B	Group C	Group D	Group E	Group F
	(I)	(2)	(3)	(4)	(5)	(6)
Per I% increase in Arrears	- 0.0019 [-0.0054, 0.0016]	- 0.0019 [-0.0054, 0.0016]	0.022*** [0.013, 0.03]	-0.00081 [0.0079, 0.0061]	0.0017 [-0.0018, 0.0052]	0.00018 [-0.0050, 0.0013]
Extraordinary transfer payment in 2014	- 0.19*** [-0.29, -0.083]	- 0.029 [-0.47, 0.41]	-0.50*** [-0.85, -0.15]	-0.32 [-0.59, -0.053]	-0.12* [-0.28, 0.041]	-0.19*** [-0.31, -0.065]
Extraordinary transfer payment in 2016	- 0.054*** [-0.084, -0.024]	- 0.315*** [-0.44, -0.19]	-0.39*** [-0.48, -0.30]	-0.27*** [-0.34, -0.20]	-0.07*** [-0.12, -0.025]	0.45*** [0.39, 0.52]

In summary, there was no significant association between a 1% increase in arrears and hospital mortality for the whole sample and for all groups estimated separately except for group C. Extraordinary transfer payments in 2014 were associated with a decrease in hospital mortality over all hospital groups. Moreover, extraordinary transfer payments in 2016 were also associated with a decrease in hospital mortality over all hospital groups except for group F, for which a significant increase in hospital mortality was estimated. The complete results of the

[13] Due to missing information and impure data recording, we do not estimate the model separately for hospitals belonging to group „Other".
[14] 95% Confidence Interval in parentheses. * p< 0.10, ** p < 0.05, *** p < 0.01.

probit regressions including the control variables are shown in Appendix 3. Moreover, in Appendix 4 we report full results of the initial model including the arrears.

To put the magnitude of these associations in perspective, the model estimates for patients treated in a hospital of group C that a 20% increase in payment arrears is, on average, associated with a 0.45% (95% CI: 0.26-0.60%) increase in hospital mortality. Hence, this increase in payment arrears has the same effect on mortality as an aging of the average patient by three years. However, this increase is offset if the hospital was subject to an extraordinary transfer payment in 2014, which is, on average, associated with a 0.50% (95% CI: 0.15-0.85%) decrease in hospital mortality. Moreover, if the hospital was subject to an extraordinary transfer payment of the government in 2016, hospital mortality was further decreased, on average, by 0.39% (95% CI: 0.30-0.48%).

6. Robustness Checks

We performed a series of robustness and specificity checks. First, we estimated a linear probability model by OLS. Results of this estimation are presented in Appendix 4 since these are not significantly different from the reported margins provided by the probit regressions. Subsequently, we further disaggregated the model by several variables. First, we examine women and men separately. In a next step, we consider only patients which are not treated ambulatory and thus, have a length of stay of at least 24 hours. As shown in Table 4 the results do not vary considerably compared to the results in Table 3 in section 5. Interestingly, the direction of the effect for increasing arrears of group C is consistent as well.

Table 4: Probit Regression Robustness Checks – Gender & Hospitalization

	Percent change in hospital mortality					
	Total			Group C		
	Men	Women	INT	Men	Women	INT
	(1)	(2)	(3)	(4)	(5)	(6)
Per I% increase in Arrears	- 0.0023 [-0.0031, 0.0026]	0.0012 [-0.0017, 0.0019]	0.0017 [-0.0044, 0.0078]	0.018** [0.0029, 0.033]	0.022*** [-0.0018, 0.0052]	0.042*** [0.021, 0.063]
Extraordinary transfer payment in 2014	- 0.25*** [-0.43, -0.078]	- 0.12** [-0.24, -0.035]	- 0.075 [-0.28, 0.43]	-0.68** [-1.27, -0.089]	-0.30 [-0.66, 0.077]	0.033 [-0.70, 0.77]
Extraordinary transfer payment in 2016	- 0.083*** [-0.13, -0.033]	- 0.027*** [-0.061, 0.0077]	- 0.27*** [-0.39, -0.17]	-0.40*** [-0.55, -0.25]	-0.33*** [-0.42, -0.27]	-0.63*** [-0.85, -0.41]

Thereafter, we further disaggregate the model by the age of patients. In the style of Loopstra et al. (2016) we estimate the model separately for three different age groups in order to see whether the most vulnerable groups of patients are significantly affected by payment arrears. As seen in Table 5 the results do reinforce the previously reported effects.

Table 5: Probit Regression Robustness Checks - Old-Age Mortality

	Percent change in hospital mortality					
	Total			Group C		
	65+	65 to 84	85+	65+	65 to 84	85+
	(1)	(2)	(3)	(4)	(5)	(6)
Per I% increase in Arrears	0.0049 [-0.0027, 0.0037]	0.0072 [-0.0023, 0.0038]	-0.0020 [-0.017, 0.013]	0.038*** [0.023, 0.053]	0.020** [0.0015, 0.031]	0.15*** [0.093, 0.21]
Extraordinary transfer payment in 2014	- 0.26** [-0.46, -0.047]	- 0.28*** [-0.47, -0.089]	- 0.28 [-1.03, 0.98]	- 0.66** [-1.26, -0.059]	- 0.50* [-1.10, 0.060]	- 1.29 [-3.50, 0.90]
Extraordinary transfer payment in 2016	- 0.23*** [-0.29, -0.17]	- 0.090*** [-0.15, -0.035]	- 1.12*** [-1.14, -0.83]	- 0.80*** [-0.95, -0.64]	- 0.57*** [-0.71, -0.42]	- 1.73*** [-2.31, -1.14]

Compared to the overall results presented in table 3 in section 5, the effects of increasing payment arrears and of extraordinary transfer payments on hospital mortality is even stronger for older inpatients.

Finally, we repeated the analysis for specific DRGs more susceptible to funding cuts. More precisely, we limited the analysis to DRG 14 (intracranial hemorrhage or cerebral infarction), DRG 89 (pneumonia) and DRG 127 (heart failure and shocks) since these have high mortality rates and a potential delay in treatment can be costly to patients' health. As shown in Table 6 the results obtained previously are not reinforced by focusing on DRGs linked to time critical treatments.

Table 6: Probit Regression Robustness Checks – Specific DRGs

	Percent change in hospital mortality		
	Total		
	DRG 14	DRG 89	DRG 127
	(1)	(2)	(3)
Per l% increase in Arrears	0.016 [-0.0064, 0.040]	-0.011 [-0.054, 0.033]	0.022 [-0.0075, 0.052]
Extraordinary transfer payment in 2014	- 0.20* [-0.46, -0.014]	- 0.41 [-2.98, 2.16]	- 0.21 [-1.75, 2.18]
Extraordinary transfer payment in 2016	- 0.20 [-0.70, 0.29]	- 0.16 [-1.03, 0.71]	- 0.14 [-0.77, 0.50]

A possible explanation for the absence of the previously estimated effects could be that high mortality DRGs may still be treated as if there were no funding cuts. Thus, there might be DRGs with a relatively lower mortality rate which are more severe affected by funding cuts. This explanation lends support to the following effect of arrears. If arrears mean less available funds in each moment, management has to use available funds for most immediate needs, without or only with little planning, which leads to less effective management and consequently higher mortality.

7. Conclusion

In this paper, we examined the relation between payment arrears as a proxy for austerity measures and in-hospital mortality. By the means of a probit model we established our main empirical findings. For four out of five hospital groups in Portugal we did not find a significant correlation between increasing payment arrears and mortality rates. In hospitals belonging to group C we found a significant relation between increasing arrears and the respective in hospital mortality rate. Consistent over almost all hospitals we found that extraordinary transfer payments by the government result in lower in-hospital mortality.

By increasing arrears hospitals are extending the budget constraint that is set by the global budget they receive from the ACSS. Thus, arrears are a way of overcoming the budget constraint. The question resulting from this is whether exceeding the budget constraint is due to underfunding or a result of inefficiency. For the groups B, D, E and F where there is no significant correlation between arrears and in-hospital mortality, it seems that arrears result from inefficiencies. Contrary, with regard to extraordinary payments it seems that it is helpful to receive additional money from the government to reduce in-hospital mortality. If they were not able to get the additional money they would have a higher mortality and in that sense austerity would be bad for these groups which is in turn a signal that they are underfunded. With respect to group C the causation is different. If they accumulate more arrears they have higher in-hospital mortality. Hence, it is possible that they could not grow payment arrears in a sufficiently large number to overcome the problems of the budget constraint. Moreover, what reinforces the argument for underfunding of these hospitals is that the extraordinary payments do in fact significantly decrease in-hospital mortality.

We aware that our research may have several limitations. The first is that one conceptual point is missing or still to be discussed. If hospitals do not care about arrears for day to day decisions on patient care it could mean that less efficient management teams need more funds to achieve good outcomes and then both arrears and higher mortality will follow. Thus, within this interpretation, arrears and mortality are associated but no causality exists. Unfortunately, we were unable to investigate the effect of arrears on hospital mortality further due to the fact that arrears data were only collected since the beginning of 2014. Future studies should aim at enhancing the quantity of arrears data of Portuguese public hospitals. Our results are promising and should be validated by a larger sample size. Moreover, this paper has given rise to many questions in need of further investigation to understand the effect of payment arrears on in-hospital mortality.

8. References

Agency for Healthcare Research and Quality. (2002). *AHRQ Quality Indicators—Guide to Inpatient Quality Indicators: Quality of Care in Hospitals - Volume, Mortality, and Utilization.* Rockville: Agency for Healthcare Research and Quality.

Aiken, L. H., Cimiotti, J. P., Sloane, D. M., Smith, H. L., Flynn, L., & Neff, D. F. (2011). The Effects of Nurse Staffing and Nurse Education on Patient Deaths in Hospitals With Different Nurse Work Environments . *Medical Care*, 1047–1053.

Aiken, L. H., Sloane, D. M., Bruyneel, L., Van den Heede, K., Griffiths, P., Busse, R., . . . McHugh, M. D. (2014). Nurse staffing and education and hospital mortality in nine European countries: a retrospective observational study . *The Lancet*, 1824–1830.

Augusto, G. (2012). Cuts in Portugal's NHS could compromise care. *Lancet*(379), 400.

Barros, P. P., Machado, S. R., & Simões, J. (2011). Portugal: health system review. *Health Systems in Transition*, 1–156.

Busse, R., Geissler, A., Quentin, W., & Wiley, M. (2011). *Diagnosis-Related Groups in Europe.* New York: McGraw-Hill.

Doyle, J. J., Graves, J., & Gruber, J. (2017). Evaluating Measures of Hospital Quality. *NBER Working Paper Series*.

European Observatory on Health Systems and Policies. (2018). *Health System Review Portugal.* Copenhagen: World Health Organization.

Gobillon, L., & Milcent, C. (2017). Competition and hospital quality: Evidence from a French natural experiment. *IZA Discussion Papers*.

Hentschker, C., & Mennicken, R. (2012). The Relationship between Quality and Hospital Case Volume. *Ruhr Economic Papers*(341).

Karanikolos, M., Mladovsky, P., Cylus, J., Thomson, S., Basu, S., Stuckler, D., . . . McKee, M. (2013). Financial crisis, austerity, and health in Europe. *The Lancet*, 1323–31.

Loopstra, R., McKee, M., Katikireddi, S. V., Taylor-Robinson, D., Barr, B., & Stuckler, D. (2016). Austerity and old-age mortality in England: a longitudinal cross-local area analysis, 2007–2013. *Journal of the Royal Society of Medicine*, 109-116.

Simões, J., Augusto, G. F., Fronteira, I., & Hernández-Quevedo, C. (2017). Portugal: Health system review. *Health Systems in Transition*, 1–184.

Stuckler, D., & Basu, S. (2013). *The Body Economic: Why Austerity Kills.* New York: Basic Books.

The Guardian. (2017, 08 27). *Lessons on austerity from all over Europe.* Retrieved 11 25, 2018, from The Guardian: https://www.theguardian.com/business/2017/aug/27/lessons-on-austerity-from-all-over-europe

9. Appendices

Appendix 1: NHS Classification of Hospital Groups

#	Group B	Group C	Group D	Group E	Group F
1	CH Povoa do Varzim/ V.C.	CH Barreiro / Montijo	CH Tondela - Viseu	CH Lisboa Norte	IPO Coimbra
2	CH Medio Ave	CH Cova da Beira	CH TM Alto Douro	CH Lisboa Central	IPO Lisboa
3	HD Figueira da Foz	CH Entre Douro e Vouga	CH VN Gaia / Espinho	CH Lisboa Ocidental	IPO Porto
4	H Santa Maria Maior	CH Medio Tejo	CH Algarve	CH de Sao Joao	-
5	ULS Guarda	CH Tamega e Sousa	H Garcia da Orta	CH do Porto	-
6	ULS Castelo Branco	CH Leiria	-	CHU de Coimbra	-
7	ULS Litoral Alentejano	CH Setubal	-	-	-
8	ULS Nordeste	CH Baxo Vouga	-	-	-
9	-	HD Santarem	-	-	-
10	-	ULS Matosinhos	-	-	-
11	-	ULS Alto Minho	-	-	-
12	-	ULS Baixo Alentejo	-	-	-
13	-	ULS Norte Alentejo	-	-	-

Appendix 2: Description of Explanatory Variables

Variable	Unit	Description
age	number of years	Specifies the age of patient p
male	dummy	Equal to 1 if patient p is male
severity2	dummy	Equal to 1 if the patient p has a severity indicator of 2 (on a 1 to 4 scale of severity, where 1 is the lowest)
severity3	dummy	Equal to 1 if the patient p has a severity indicator of 3 (on a 1 to 4 scale of severity, where 1 is the lowest)
severity4	dummy	Equal to 1 if the patient p has a severity indicator of 4 (on a 1 to 4 scale of severity, where 1 is the lowest)
utilization	in percent	Indicates the monthly occupancy rate of hospital h
hosp_south	dummy	Equal to 1 if the treating hospital h is lcoated in the south of the country
FEB	dummy	Equal to 1 if patient p is treated in February
MAR	dummy	Equal to 1 if patient p is treated in March
APR	dummy	Equal to 1 if patient p is treated in April
MAY	dummy	Equal to 1 if patient p is treated in May
JUN	dummy	Equal to 1 if patient p is treated in June
JUL	dummy	Equal to 1 if patient p is treated in July
AUG	dummy	Equal to 1 if patient p is treated in August
SEP	dummy	Equal to 1 if patient p is treated in September
OCT	dummy	Equal to 1 if patient p is treated in October
NOV	dummy	Equal to 1 if patient p is treated in November
DEC	dummy	Equal to 1 if patient p is treated in December
JUL_south	dummy	Equal to 1 if patient p is treated in July and the treating hospital h is located in the south of the country
AUG_south	dummy	Equal to 1 if patient p is treated in August and the treating hospital h is located in the south of the country
Arrears	100.000 EUR	Indicates the monthly level of arrears of the treating hospital h
l1_Arrears	100.000 EUR	Indicates the level of arrears of hospital h three months ago
l2_Arrears	100.000 EUR	Indicates the level of arrears of hospital h six months ago
l3_Arrears	100.000 EUR	Indicates the level of arrears of hospital h nine months ago
delta_Arr	100.000 EUR	Indicates the monthly change in the level of arrears of hospital h (equal to 0 if capital inflow is present)
Inflow_2014	dummy	Equal to 1 for every month after the first large capital inflow happened (2014)
Inflow_2016	dummy	Equal to 1 for every month after the second large capital inflow happened (2016)

Appendix 3: Margins after Probit Regression (Adjusted Framework)

	Marginal Effects after Probit					
	Total	Group B	Group C	Group D	Group E	Group F
	(I)	(2)	(3)	(4)	(5)	(6)
age	**.0007136***** (126.33)	**.001319***** (49.66)	**.0014665***** (80.05)	**.0008952***** (63.40)	**.0004164***** (50.69)	**.0000772***** (17.93)
male	**.0028443***** (20.75)	**.0042047***** (7.18)	**.0033809***** (7.84)	**.0033089***** (9.88)	**.0027491***** (12.53)	**.0008897***** (6.46)
severity 2	**.0365787***** (125.15)	**.064086***** (46.88)	**.048368***** (62.57)	**.0340935***** (53.31)	**.0296609***** (55.90)	**.0158297***** (40.34)
severity 3	**.2442228***** (169.23)	**.2525192***** (58.05)	**.2493436***** (85.57)	**.2639957***** (79.68)	**.2110501***** (84.25)	**.4162567***** (68.63)
severity 4	**.56202***** (225.51)	**.5311036***** (58.29)	**.5717846***** (111.94)	**.5659338***** (104.12)	**.5787257***** (141.04)	**.626706***** (48.28)
utilization	**.0000971***** (8.90)	**.0000919***** (2.78)	**.0002613***** (8.79)	**-.0001667***** (-3.01)	**8.15e-06** (0.43)	**.0001168***** (8.97)
hosp_south	**.012498***** (23.43)			**.0164101***** (24.48)		
FEB	**-.0013596***** (-4.55)	**-.0022576** (-1.79)	**-.003189***** (-3.46)	**-.0028941***** (-3.91)	**-.0002921** (-0.59)	**-.0001484** (-0.45)
MAR	**-.003366***** (-12.24)	**-.0015191** (-1.14)	**-.0077655***** (-9.37)	**-.0052798***** (-8.06)	**-.0017722***** (-3.80)	**-.0003888** (-1.33)
APR	**-.003312***** (-11.82)	**-.0034972** (-2.75)	**-.0070411***** (-8.17)	**-.005121***** (-7.52)	**-.0016082***** (-3.37)	**-.0006091**** (-2.14)
MAY	**-.0032609***** (-11.55)	**-.0023401*** (-1.77)	**-.0082724***** (-9.96)	**-.0055218***** (-7.81)	**-.0016262***** (-3.40)	**-.0003682** (-1.20)
JUN	**-.003544***** (-12.70)	**-.0044719***** (-3.64)	**-.0087748***** (-10.64)	**-.0061647***** (-9.16)	**-.0015574***** (-3.24)	**-1.49e-06** (-0.00)
JUL	**-.00374***** (-13.14)	**-.0039397***** (-3.01)	**-.009541***** (-11.77)	**-.0048072***** (-6.22)	**-.0024356***** (-5.18)	**-.0006484**** (-2.32)
AUG	**-.0027481***** (-9.22)	**-.0023484*** (-1.74)	**-.0082008***** (-9.77)	**-.0042695***** (-5.30)	**-.001282**** (-2.54)	**.0000437** (0.13)
SEP	**-.0028497***** (-9.70)	**-.0028628**** (-2.12)	**-.0096067***** (-11.68)	**-.0041984***** (-5.49)	**-.000749** (-1.45)	**.0001012** (0.31)
OCT	**-.0028519***** (-10.38)	**-.0040695***** (-3.38)	**-.0081895***** (-10.24)	**-.0053425***** (-7.63)	**-.0008837*** (-1.85)	**.0001628** (0.53)
NOV	**-.0027658***** (-9.34)	**-.0016809** (-1.22)	**-.006128***** (-6.91)	**-.0058111***** (-8.03)	**-.0009232*** (-1.75)	**-.0010798***** (-4.27)
DEC	**.0005355***** (1.65)	**.0024418*** (1.66)	**.0022677**** (2.23)	**-.0012339** (-1.45)	**.0015413***** (2.81)	**-.0012979***** (-5.93)
JUL_south	**.0049671***** (3.56)			**.0041609**** (2.43)		
AUG_south	**-.0000681** (-0.06)			**-.0006422** (-0.44)		
delta_Arr	**7.48e-08** (0.01)	**-.0000186** (-1.04)	**.000218***** (4.94)	**-8.91e-06** (-0.25)	**.0000168** (0.94)	**-.0000183** (-1.14)
Inflow 14	**-.0018815***** (-3.52)	**-.0002859** (-0.13)	**-.0050059***** (-2.83)	**-.0031981**** (-2.35)	**-.0011923** (-1.46)	**-.0018734***** (-3.00)
Inflow 16	**-.0005368***** (-3.50)	**-.0031473***** (-4.97)	**-.0038644***** (-8.47)	**-.0026967***** (-7.57)	**-.0007445***** (-2.92)	**.0045432***** (13.14)

Appendix 4: Margins after Probit Regression (Initial Framework)

	Marginal Effects after Probit					
	Total	Group B	Group C	Group D	Group E	Group F
	(I)	(2)	(3)	(4)	(5)	(6)
age	.0006999***	.0013191***	.0014655***	.0008905***	.0004138***	.0000721***
	(124.62)	(49.62)	(80.11)	(50.68)	(50.68)	(17.11)
male	.0027899***	.0042043***	.0033629***	.0033356***	.0027379***	.0008166***
	(20.51)	(7.19)	(7.81)	(9.97)	(12.57)	(6.16)
severity 2	.0366963***	.0639381***	.0485346***	.0345921***	.0296114***	.0151231***
	(125.82)	(46.43)	(62.78)	(53.38)	(55.95)	(38.55)
severity 3	.248303***	.2521703***	.2507488***	.2647536***	.2130972***	.4103478***
	(169.72)	(57.84)	(85.65)	(79.52)	(84.27)	(67.24)
severity 4	.573025***	.5307104***	.5734308***	.5684267***	.583774***	.6236365***
	(227.48)	(58.17)	(112.26)	(104.28)	(141.95)	(47.70)
utilization	.0000829***	.0000726**	.0001982***	-.0002217***	-.000013	.0001239***
	(7.68)	(2.18)	(6.23)	(-3.81)	(-0.69)	(8.92)
hosp_south	.0097757***			.0155859***		
	(19.69)			(20.81)		
FEB	-.0012828***	-.0020997*	-.0031532***	-.0026582***	-.0003408	-.0001226
	(-4.31)	(-1.65)	(-3.42)	(-3.54)	(-0.70)	(-0.37)
MAR	-.003189***	-.0006929	-.0071373***	-.0052133***	-.0010827**	-.0004433
	(-11.12)	(-0.50)	(-8.19)	(-7.69)	(-2.11)	(-1.44)
APR	-.0033084***	-.0027465**	-.0067138***	-.0051862***	-.001102**	-.0007182**
	(-11.80)	(-2.07)	(-7.56)	(-7.54)	(-2.19)	(-2.53)
MAY	-.003155***	-.0016716	-.008005***	-.0056051***	-.0009549*	-.000236
	(-11.55)	(-1.22)	(-9.48)	(-7.96)	(-1.87)	(-0.74)
JUN	-.0032797***	-.0033878**	-.008423***	-.0062176***	-.0006398	.000242
	(-11.27)	(-2.50)	(-10.01)	(-9.08)	(-1.15)	(0.68)
JUL	-.0033267***	-.0029517**	-.0091887***	-.0045708***	-.0014545***	-.0004715
	(-11.23)	(-2.09)	(-11.08)	(-5.72)	(-2.73)	(-1.51)
AUG	-.0023672***	-.0016663	-.0078097***	-.0039942***	-.0003513	.0004024
	(-7.71)	(-1.17)	(-9.07)	(-4.83)	(-0.63)	(1.07)
SEP	-.0024422***	-.0027869**	-.0085985***	-.0040359***	-.000757	.0004423
	(-8.14)	(-2.00)	(-9.96)	(-5.10)	(-1.44)	(1.23)
OCT	-.002359***	-.0041451***	-.0071153***	-.0048162***	-.0004657	.0004804
	(-8.33)	(-3.36)	(-8.48)	(-6.53)	(-0.92)	(1.41)
NOV	-.0023469***	-.0015497	-.0051106***	-.0053884***	-.0003519	-.0007105**
	(-7.72)	(-1.09)	(-5.50)	(7.12)	(-0.63)	(-2.51)
DEC	-.0000283	.0020897	.0019994**	-.0019572**	.0008679	-.0012996***
	(-0.09)	(1.43)	(1.98)	(-2.34)	(1.63)	(-6.25)
JUL_south	.0036614***			.0025148		
	(2.77)			(1.52)		
AUG_south	-.0009016			-.0019957		
	(-0.83)			(-1.45)		
Arrears	-.0001294***	.0000252	-.0002313***	-.0002198***	-.0000327***	-.0001004***
	(-16.31)	(0.17)	(-6.04)	(-5.00)	(-3.89)	(-3.06)
l1_Arrears	.0000465***	.0003189	.0001051**	.0000304	.0000255**	-.0000992**
	(4.29)	(1.58)	(1.98)	(0.52)	(2.27)	(-1.97)
l2_Arrears	-.0000236**	.0000878	.0000372	-7.99e-06	.0000152	.0001161**
	(-2.12)	(0.42)	(0.70)	(-0.14)	(1.31)	(2.35)
l3_Arrears	.0000349***	-.0004502***	.000174***	.0000166	-.0000449***	.000012
	(4.30)	(-2.96)	(4.76)	(0.38)	(-5.23)	(0.29)
delta_Arr	-5.35e-06	-.0000189	.0002511	-9.21e-06	-.0000111	-.0000371**
	(-0.66)	(-1.06)	(5.63)	(-0.25)	(-0.61)	(-2.33)
Inflow 14	-.0020781***	.0001673	-.0050095***	-.0041729***	-.0005493	-.0010784**
	(-3.86)	(0.08)	(-2.81)	(-2.94)	(-0.70)	(-1.96)
Inflow 16	.0000459	-.0034928***	-.0024586***	-.0011278***	-.000119	.0050774***
	(0.29)	(-5.41)	(-5.13)	(-2.77)	(-0.44)	(14.31)

Appendix 5: OLS Regression Results

	Marginal Effects after Probit					
	Total	Group B	Group C	Group D	Group E	Group F
	(I)	(2)	(3)	(4)	(5)	(6)
age	.0009032***	.0013539***	.0013416***	.0010555***	.0006019***	.0002071***
	(133.27)	(51.52)	(77.89)	(64.92)	(55.21)	(20.21)
male	.0011877***	.0019741*	-.0017266***	.0015587***	.0024874***	.0014674***
	(4.60)	(1.94)	(-2.54)	(2.64)	(5.62)	(4.35)
severity 2	.0257162***	.0514697***	.0327909***	.0221265***	.015841***	.0149852***
	(127.28)	(50.83)	(63.15)	(49.10)	(51.08)	(40.61)
severity 3	.2034719***	.2245874***	.21239***	.2220703***	.1546464***	.3495945***
	(224.23)	(74.74)	(115.34)	(108.68)	(113.33)	(70.15)
severity 4	.4576417***	.4384304***	.4681249***	.4606933***	.4505119***	.5236718***
	(214.59)	(53.35)	(105.86)	(100.28)	(139.71)	(39.79)
utilization	.0002436***	.0001686***	.0004778***	-.0003166***	-1.25e-06	.0006324***
	(11.09)	(2.85)	(9.86)	(-3.35)	(-0.03)	(8.07)
hosp_south	.0251308***			.028628***		
	(27.61)			(29.22)		
FEB	-.0030121***	-.0039643	-.0063403***	-.00592***	-.0009462	.0006772
	(-4.35)	(-1.49)	(-3.44)	(-3.59)	(-0.81)	(0.74)
MAR	-.0075674***	-.0031366	-.0157403***	-.010882***	-.0043785***	-.0007999
	(-11.39)	(-1.18)	(-8.94)	(-7.03)	(-3.84)	(-0.94)
APR	-.0076446***	-.0076573***	-.01408***	-.0110771***	-.0042432***	-.0014467*
	(-11.36)	(-2.92)	(-7.82)	(-6.95)	(-3.65)	(-1.69)
MAY	-.0076758***	-.0055897**	-.017418***	-.0114813***	-.0040348***	-.0009526
	(-11.54)	(-2.15)	(-9.95)	(-7.03)	(-3.55)	(-0.99)
JUN	-.0081585***	-.0084577***	-.0184122***	-.0129587***	-.003606***	-.0000779
	(-12.27)	(-3.32)	(-10.57)	(-8.10)	(-3.13)	(-0.09)
JUL	-.0084552***	-.0078638***	-.0188467***	-.0095548***	-.005926***	-.002247***
	(-12.60)	(-2.93)	(-10.78)	(-5.72)	(-5.04)	(-2.65)
AUG	-.0063629***	-.0051982*	-.0167541***	-.0086441***	-.0030621**	-.0008955
	(-9.25)	(-1.92)	(-9.35)	(-4.98)	(-2.47)	(-1.03)
SEP	-.0067101***	-.0067249**	-.0192383***	-.0088997***	-.0021951*	-.0004406
	(-10.11)	(-2.52)	(-11.04)	(-5.27)	(-1.89)	(-0.51)
OCT	-.006686***	-.0085644***	-.0163228***	-.0109492***	-.0026165**	-.0000674
	(-10.69)	(-3.51)	(-9.86)	(-6.89)	(-2.39)	(-0.08)
NOV	-.0064537***	-.004524*	-.0125356***	-.0119025***	-.0030447***	-.0042156***
	(-9.70)	(-1.71)	(-7.20)	(-7.13)	(-2.65)	(-4.89)
DEC	.0007352	.0034709	.003011	-.0021145	.0026198**	-.0035158***
	(1.05)	(1.28)	(1.64)	(-1.20)	(2.16)	(-3.98)
JUL_south	.0089188***			.0065811**		
	(2.84)			(2.00)		
AUG_south	-.0030686			-.0039657		
	(-1.04)			(-1.27)		
delta_Arr	-3.98e-06	-.0000309	.0004409***	.0000105	4.15e-06	-.0000328
	(-0.23)	(-0.98)	(4.15)	(0.18)	(0.16)	(-0.79)
Inflow 14	-.0029512***	-.001171	-.0060076**	-.0057208***	-.0020349	-.0055164***
	(-3.29)	(-0.31)	(-2.51)	(-2.75)	(-1.33)	(-4.77)
Inflow 16	-.0010878***	-.0042311***	-.0059919***	-.0054149***	-.001698***	.0085137***
	(-3.64)	(-3.72)	(-8.43)	(-8.46)	(-3.39)	(11.84)
Constant	-.0626792***	-.0863804***	-.0935561***	-.0191233**	-.0274444***	-.0592728***
	(-28.75)	(-12.47)	(-17.82)	(-2.09)	(-6.89)	(-9.12)